

Comparison of Cell formation techniques in Cellular manufacturing using three cell formation algorithms

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ABSTRACT

In the present era of globalization and competitive market, cellular manufacturing has become a vital tool for meeting the challenges of improving productivity, which is the way to sustain growth. Getting best results of cellular manufacturing depends on the formation of the machine cells and part families. This paper examines advantages of ART method of cell formation over array based clustering algorithms, namely ROC-2 and DCA. The comparison and evaluation of the cell formation methods has been carried out in the study. The most appropriate approach is selected and used to form the cellular manufacturing system. The comparison and evaluation is done on the basis of performance measure as grouping efficiency and improvements over the existing cellular manufacturing system is presented.

Keywords - Neural Network, ART Model, Group Technology

I. INTRODUCTION

Group Technology is a manufacturing philosophy in which similar parts are identified. Machines on which these parts are to be processed are grouped together to form a GT cell. The purpose of GT cell is that the Cellular manufacturing system is result of implementation of GT to the production. The number of benefit has been achieved by implementation of CMS, like material handling, cost reduction; work in process inventory reduction, set-up time reduction, and equipment cost reduction, direct/indirect labor cost reduction, improvement of quality, improvement in space utilization and employees satisfaction etc.

Formation of part families and machine cells is the key step towards the design of cellular manufacturing system (CMS). The input data are derived from route sheet. These data are in the form of zero-one matrices. The rows represent the machines and columns represent parts. Elements of the matrix 'a_{ij}' will be '1' if the jth component is processed on ith machine. If it is not 'a_{ij}' will be zero. The output is obtained in the form of block diagonal structure. Each block represents a machine cell and a part family. Number of research work has been done in the last decades for cell formation. The researchers have proposed number of algorithms for cell formation using production flow analysis. In this paper it is presented that ART algorithm is found better over array based cell formation techniques.

II. LITERATURE SURVEY

Survey of literature has been carried out to identify the findings and directions given by researchers. The contribution and directions of

selected research work reported in the literature have been presented below:

The problem was originally identified by Murthy and Srinivasan [1]. They used simulated annealing (SA) and heuristics algorithms (HA) for fractional cell formation. In other research, Srinivasan and Zimmers [2] used a neighborhood search algorithm for fractional cell formation.

The architecture of the ART1 is based on the idea of adaptive resonant feedback between two layers of nodes, as developed by Grossberg [3]. The ART1 Model described in Carpenter and Grossberg [4] was designed to cluster binary input patterns. Dagli and Huggahalli [5] and Chen and Park [6] also modified the ART1 in their works to improve its performance in GT cell formation. But their modifications are not suitable for fractional cell formation. Miin-Shen Yang and Jenn- Hwai Yang [7] proposed a modified ART1 neural learning algorithm. In modified ART1, the vigilance parameter can be simply estimated by the data so that it is more efficient and reliable than Dagli and Huggahalli's method for selecting a vigilance value.

M. Murugan and Selladurai[8] proposed an Art Modified Single Linkage Clustering approach (ART-MOD-SLC) to solve cell formation problems in Cellular Manufacturing. In this study, an ART1 network is integrated with Modified Single Linkage Clustering (MOD-SLC) to solve cell formation problems. The Percentage of Exceptional Elements (PE), Machine Utilization (MU), Grouping Efficiency (GE) and Grouping Efficacy (GC) are considered as performance measures. This proposed heuristic ART1 Modified Single Linkage Clustering (ART-MOD-SLC) first constructs a cell formation

using an ART1 and then refines the solution using Modified Single Linkage Clustering (MOD-SLC) heuristic. ART1 Modified Single Linkage Clustering has been applied to most popular examples in the literature including a real time manufacturing data. According to P. Venkumar and A. Noorul Haq [9] the GT cell formation by any known algorithm/heuristics results in much intercell movement known as exceptional elements. In such cases, fractional cell formation using reminder cells can be adopted successfully to minimize the number of exceptional elements. The fractional cell formation problem is solved using modified adaptive resonance theory1 network (ART1). The input to the modified ART1 is machine-part incidence matrix comprising of the binary digits 0 and 1. This method is applied to the known benchmarked problems found in the literature and it is found to be equal or superior to other algorithms in terms of minimizing the number of the exceptional elements. The relative merits of using this method with respect to other known algorithms/heuristics in terms of computational speed and consistency are presented. Yong Yina and Kazuhiko Yasudab[10] gave a comprehensive overview and discussion for similarity coefficients developed to date for use in solving the cell formation (CF) problem. Despite previous studies indicated that similarity coefficients based method (SCM) is more flexible than other CF methods, none of the studies has explained the reason why SCM is more flexible. They tried to explain the reason explicitly. They also developed a taxonomy to clarify the definition and usage of various similarity coefficients in designing CM systems. Existing similarity (dissimilarity) coefficients developed so far are mapped onto the taxonomy. Additionally, production information based similarity coefficients are discussed and a historical evolution of these similarity coefficients is outlined. Finally, recommendations for future research are suggested. Chang-Chun Tsai and Chung-ying Leewe [11] presented a multi-functional MP (mathematical programming) model that incorporates the merits of related CF (Cell Formation) models based on the systematic study of MP models. The proposed model can offer the suitable modules that include the different objective functions and constraints for user to solve the related problem. In addition, analysis results demonstrate that the proposed model's performance to outperform the other related models. Jose Fernando Goncalves and Mauricio G.C. Resende [12] presented a new approach for obtaining machine cells and product families. The approach combines a local search heuristic with a genetic algorithm. Computational experience with the algorithm on a set of group technology problems available in the literature is also presented the approach produced solutions with a grouping efficacy

that is at least as good as any results previously reported in literature and improved the grouping efficacy for 59% of the problems.

III. METHODOLOGY

Proposed methodology uses the Adaptive Resonance Theory (ART) neural network to solve the cell formation problem in group technology (GT). The advantage of using an ART network over the other conventional methods, like ROC (Rank order clustering) and DCA (Direct clustering Analysis) are the fast computation and outstanding ability to handle large-scale industrial problems.

A. Rank order clustering2 (ROC-2)

ROC-2 was developed by King and Nakoranchai (1982) to overcome the limitations of ROC. ROC-2 can identify block diagonal structure (of machine part incidence matrix) very quickly. Therefore it is found practicable to apply in an interactive manner even for large matrices.

Algorithm:

- Step 1 Start from the last column, move the rows with positive entries to the top of the matrix.
- Step 2 Repeat step 1 for all the columns.
- Step 3 Start from the last row, move the columns with positive entries to the left of the matrix.
- Step 4 Repeat step 3 for all rows.
- Step 5 Compare the matrix with the previous result. If the matrices are different go to step 1 otherwise go to Step 6.
- Step6 Print the final machine-component incidence matrix.

B. Direct clustering analysis (DCA):

In this method, the initial matrix is rearranged according to the row and column assignments. After rearrangement the rows and columns are rearranged to form the clustered part- machine incidence matrix.

Algorithm:

- Step 1 The row and column ranks are found by adding their corresponding positive entries.
- Step 2 The matrix is rearranged according to the ranks.
- Step 3 Start from the first row, move the columns with positive entries to the left of the matrix
- Step 4 Repeat the step 3 for all the rows.
- Step 5 Start from the first column, move the rows with positive entries to the top.
- Step 6 Repeat the step 5 for all the columns.
- Step 7 Compare the matrix with the previous result. If the matrices are different go to step 3 otherwise go to step 8.
- Step 8 Print the final machine component incidence matrix

C. Adaptive Resonance Theory (ART) :

An artificial neural network is built on a number of simple processing elements called neurons. These neurons are often recognized into a sequence of layers. All layers of the network are linked by weights, which are adapted using a learning algorithm. The structure of a neural network could be characterized by interconnection architecture among neurons, the activation function for conversion of input into outputs, and the learning algorithm.

Algorithm:

Step1 : Define the number of neurons in the input layer N_{in} and number of neurons in the output layer N_{out} and select a value for vigilance parameter, ρ
 N_{in} = the number of columns (parts) of machine-part incidence matrix.
 N_{out} = the maximum expected number of machine cells.

Step 2 : Enable all the output units and initialize top down weights W^t and bottom up weights W^b

$$W^t_{ij} = 1 = t_{ij}(0)$$

$$W^b_{ij} = \frac{1}{1 + N_{in}} = b_{ij}(0) = \frac{1}{1 + N}$$

W^t_{ij} = top down weight from neuron j in the output layer to neuron i in the input layer.

W^b_{ij} = Bottom -up weight from neuron i in the input to neuron j in the output layer.

Step3 : Present a machine vector X to input layer , X consist of zero/one element x_i .

Step4: compute machining scores for all the enabled output nodes

$$Net_j = \sum_i W^b_{ij} x_i$$

Where Net_j is the output of neuron j in the output layer

Step5: Select a node with the largest value of matching score as best matching exemplar let this node be j' . In the event of a tie, the unit on the left is selected

$$Net_{j'} = \max \{ net_j \}$$

Step6: Vigilance test (i.e test of similarity with best matching exemplar)

Compute the following:

$$\|X\| = \sum_i x_i \text{ (norm of vector } X)$$

$$\|W^t_{j'} \cdot X\| = \sum W^t_{ij'} \cdot x_i$$

Let X = New pattern and Y = exemplar

So the Euclidean distance = $\sqrt{(x_i - y_i)^2}$

If $\sqrt{(x_i - y_i)^2} \leq \rho$, go to step 8, else go to step 7.

Step7: Disable best exemplar temporarily

Since the vector X does not belong to cluster j' , the output of node j' selected in step 5 is temporarily disabled and removed from future competitions; go to step4.

Step8: Adapt best matching exemplar

$$W^b_{ij'} = \frac{W^t_{ij'} \cdot x_i}{0.5 + W^t_{ij'} \cdot x_i}$$

Step9: Enable any node s disabled in step7 and go to step3.

D. Measure of Performance

To measure the efficiency of the group grouping efficiency is considered as measuring parameter represented by η ,

$$\eta = q\eta_1 - (1 - q)\eta_2$$

Where

$$\eta_1 = \frac{e_d}{\sum_{r=1}^k M_r N_r} \quad \eta_2 = 1 - \left(\frac{e_0}{mn - \sum_{r=1}^k M_r N_r} \right)$$

m = Number of machines (rows)

n = Number of parts (columns)

M_r = Number of machines in the r -th cell

N_r = Number of parts in the r -th family

e_d = Number of 1's within the machine /parts group

e_0 = Number of 1's outside the machine/parts group

k = Number of clusters

η = Grouping efficiency

q = Weighting factor ($0 < q < 1$)

Grouping efficiency (GE) ranges from 0 to 1. A GE with a value closed to 1.0 means that the solution matrix has a perfect structure. In this paper the solutions are evaluated in terms of GE and Exceptional Element (EE).

IV. TEST PROBLEMS

To check the efficiency and working of proposed methodology, few test problems are generated randomly

Problem No.	Matrix Size	Minimum Threshold
1	20x15	0.9
2	20x15	0.5
3	20x15	0.6
4	20x15	0.7

The results obtained are given in table below.

Problem No.	Calculated efficiency (%) by ART algorithm	Calculated efficiency(%) by DCA algorithm	Calculated efficiency (%) by ROC algorithm
1	72.00	63.23	67.00
2	66.15	52.00	62.24
3	66.00	61.08	65.14
4	61.50	58.25	59.28

V. CONCLUSION

The neural network based on adaptive resonance theory (ART) can be effectively used for machine-part cell formation using the information from route sheet of parts. The industries seeking to reframe their existing facilities to cellular layout can derive maximum benefit from the proposed methodology. Usually the implementation of GT is a continuous process. Different methods may be found more useful or can give better results for different kind of products. The neural network can effectively execute the dynamic characteristic of GT implementation.

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